International Journal of Innovative Research in Computer Science & Technology (IJIRCST)
ISSN: 2347-5552, Volume-2, Issue-6, November-2014

Nonlinear Process Identification and Control Using Neural Networks

Miss.Mali Priyadarshani S., Mrs. Tirmare Aarti H., Miss. Mohite Sangita R.

Abstract— In industry process control, the model identification and predictive control of nonlinear systems are always difficult problems. This necessitates the development of empirical nonlinear model from dynamic plant data. This process is known as 'Nonlinear System Identification'. Artificial neural networks are the most popular frame-work for empirical model development. The model is implemented by training a Multi-Layer Perceptron Artificial Neural network (MLP-ANN) with input output experimental data. Satisfactory agreement between identified and experimental data is found and results shown that the neural model successfully predicts the evolution of the product composition. Trained data available from nonlinear system used for process control using Model Predictive Control (MPC) algorithm. The Simulation result illustrates the validity and feasibility of the MPC algorithm.

***Index Terms*—Neural networks, NARX model identification, MLP.**

I. Introduction

This topic consist the application of Artificial Neural Networks (ANN) based Model Predictive Control (MPC) scheme to control a nonlinear system. In recent year, the requirement for the quality of automatic control in the process industries increased significantly due to the increased complexity of the plants and sharper specification of product quality. At the same time, the available computing power is increased to a very high level. Intelligent and model based control techniques are developed to obtain tighter control for such applications.

Such as Model Predictive Control (MPC), Internal Model Control (IMC), global linearization and generic model control [1]. Model Predictive Control refers to class of algorithms in which dynamic process model is used to predict and optimize process performance.MPC is well suited for high performance control of constrained multivariable processes because constraints can be incorporated directly into the associated open-loop optimal control problem. The critically important issue is to generate a more accurate nonlinear model for process prediction and optimization problem. In many applications, lack of process knowledge and/or a suitable dynamic simulator precludes the derivation of fundamental model. This process is known as nonlinear system identification. A fundamental difficulty associated with the empirical modeling approach is the selection of a suitable model form. Artificial neural networks are the most popular frame-work for empirical model development [8].

II. Nonlinear Process Identification

The use of neural networks offers some useful properties and capabilities such as: Nonlinearity, Input-Output mapping, Adaptivity, Fault tolerance. There are large numbers of neural network algorithms available. These algorithms include: multilayer perceptron (Backpropagation
Networks), Radial Basis Functions (RBF) networks, Hopfield networks and adaptive resonance networks. Of all these networks, the backpropagation and Radial Basis Function networks have been applied in most process control applications. Multilayer perceptrons have been applied successfully to solve some difficult and diverse problems by training them in a supervised manner with a highly popular algorithm known as the error backpropagation algorithm. This algorithm is based on error correction learning rule. [3], [4], [5].In general, parameters in a dynamic model, regardless of the form of its mathematical representation, can be estimated by two different approaches: a series-parallel and a parallel identification method. In most of the neural network applications, a multilayer feedforward network is employed as a nonlinear autoregressive with exogenous input model (NARX), in which the network uses a number of past (delayed) plant inputs and outputs to predict the future system output. A NARX model is a subset of the general NARMAX model [1] in which additional moving average terms are present for modeling the stochastic components of a dynamic process. Neural Networks are typically over parameterized; an important training issue that arises involves when to stop the training. A simplified version of the statistical technique of cross validation, called test set validation is usually employed. [2]

2.1. Model Identification Steps

The first phase of the work will be generation of empirical model using neural network. The critically important issue is to generate a more accurate nonlinear model for process prediction and optimization problem.

Manuscript received November 21,2014

Miss.Mali Priyadarshani S., Assistant Professor, E & TC Department, Bharati Vidyapeeth's College of Engineering, Kolhapur, Maharashtra, India
Mrs. Tirmare Aarti H., Assistant Professor, E & TC Department, Bharati Vidyapeeth's College of Engineering, Kolhapur, Maharashtra, India
Miss. Mohite Sangita R. Assistant Professor, E & TC Department, Bharati Vidyapeeth's College of Engineering, Kolhapur, Maharashtra, India

2.1.1. Structure Selection

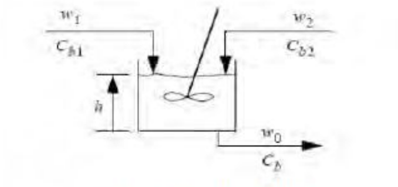


Figure 1. Continuous Stirred Reactor (CSTR)

$$\frac{dh(t)}{dt} = w_1(t) + w_2(t) - 0.2\sqrt{h(t)}$$

$$\frac{dC_b(t)}{dt} = (C_{b1} - C_b(t))\frac{w_1(t)}{h(t)} + (C_{b2} - C_b(t))\frac{w_2(t)}{h(t)} - \frac{k_1(t)C_b(t)}{(1+k_2C_b(t))^2}$$

Where h (t) is the liquid level, Cb (t) is the product concentration at the output of the process, w_1 (t) is the flow rate of the concentrated feed Cb_1, and w_2 (t) is the flow rate of the diluted feed Cb_2.

2.1.2. Input sequence design

Determination of input sequence which is injected into the plant to generate the output sequence. The data set that is used is split into two parts, one for training and one for testing. [9]

2.1.3. Parameter Estimation

In this step estimation of model parameters is done by training the neural network. The initial training of neural network is typically done using backpropagation algorithm. Periodically, one stops training the network and calculates the error that the network with its current parameters produces on the testing data. Training is terminated when a minimum in the test set error is observed. By using this train-test approach, the fact that a network has too many parameters dose not results in a problem and accurate models can be achieved. A backpropagation feedforward network is used to model a single-input-single-output (SISO) system in the series-parallel approach and an external recurrent network resulting from the parallel identification of a feedforward network for an SISO system. [6], [7], [9].

2.1.4. Model Validation

Second part of data set is used for validation of the model. After application of input signal generated output from process and model are compared here. If the comparison is good then we can replace process by its equivalent model in process control.[9]

III. Nonlinear Process Control

The main task of this work is to design a neural network controller which keeps the system stabilized. To control the nonlinear system use different approaches, such as: Model Predictive Control (MPC), Global Linearizing Feedback (GLF), and Generic Model Control (GMC).In this Model Predictive Control (MPC) is selected. In Model Predictive Control (MPC), model is used as a reference for controlling the plant.[9]

3.1. Model Predictive Control

The concept of model predictive control (MPC), in which a model is used as a reference for controlling the plant. Model predictive control represented in the Internal Model Control (IMC) structure allows the plant/model mismatch to be considered explicitly in the control problem formulation [4],[5].

3.1.1. Model Predictive Control approach

The basic idea is that a set of M control moves is calculated at every control interval so as to minimize an objective function defining the performance criterion over a prediction horizon (P steps into the future), and the first control move is implemented.

3.1.2. Model Predictive Control Formulation

In Nonlinear MPC is a formulated using nonlinear programming (NLP) technique.

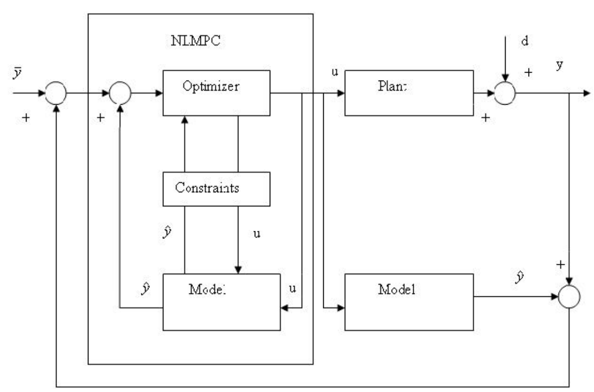


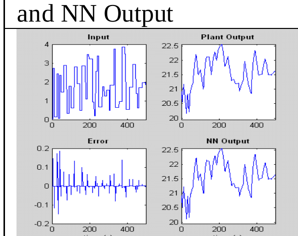
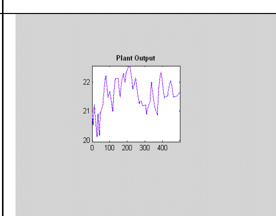
Figure 2. Structure of NLMPC Controller

Fig.2. illustrates a general IMC structure for an NLMPC algorithm. The various NLMPC algorithms differ in the way that the nonlinear model with constraints is solved.

IV. Simulation Results

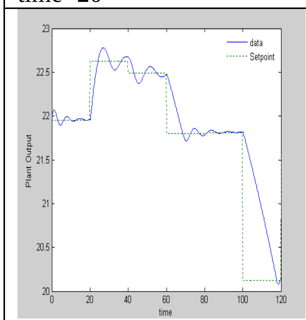
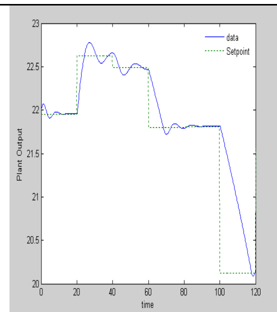
1.Model Validation

TABLE 1. Size of Hidden Layer=7, Sampling interval=1, Training Samples=2000

Comparison of Plant Output and NN Output	Validation data
	

Data set divided into two parts training and testing. Second part of data set is used for validation of the model. After application of input signal generated output from process and model are compared here. If the comparison is good then we can replace process by its equivalent model in control process.

TABLE 2.Different Control Horizon and same Prediction Horizon, Sample time

<table>
<tr><td>Prediction Horizon=5,Control Horizon=2,Sample time=20</td><td>Prediction Horizon=5,Control Horizon=3,Sample time=20</td></tr>
<tr><td>
</td><td>
</td></tr>
</table>

In Nonlinear Model Predictive Control, trained data are available from nonlinear process identification and used to control the nonlinear system for different prediction and same control horizon, sample time.

V. CONCLUSION

In this paper we discussed about neural networks and their use for nonlinear identification and control. This paper has explored in depth the use of multilayer perceptron networks for dynamic modelling and control. Neural networks can be used to develop models from data. Initial results on their use in process control have shown neural networks to be very robust to modelling errors. Once a process model is available then it can be used in many ways to improve process operation.

ACKNOWLEDGMENT

It is a huge pleasure for me to express my deep gratitude and sincere thanks to my guide for her valuable and useful guidance, on my work.

REFERENCES

[1] Su.H.T. & McAvoy.T.J., (1997) .Artificial Neural Networks for nonlinear Process Identification and Control". In Henson, M.A., &Seaborg, D.E. (Eds).Nonlinear process control, Chapter 7(pp.371-428).Englewood Cliffs, NJ: Prentice-Hall.

[2] Michael A.Henson (1998).Nonlinear model predictive control: current status and future directions.

[3] Martin T.Hagan, Howar B.Demuth.*Neural Networks for Control.*

[4] Rihab Khalid Al Seyab (2006).Nonlinear Model Predictive Control Using Automatic Differentiation.

[5] Stephen Piche &, Bijan Sayyar-Rodsari, Doug Johnson, arid Mark Gerules. *Nonlinear model predictive control using neural networks.*

[6] J.C.Hokins and D.M.Himmelblau.Artificial neural network models of knowledge representation in chemical engineering. *Computers & Chemical Engineering*.12:881-890.1988.

[7] K.Hornik, M.Stinchcombe, and H.White.Multilayer feedforward networks are universal approximatros.*Neural Networks*, 2(5):359-366, 1989.

[8] M.Pottmann and D.Seborg.A radial basis function control strategy and its application to a ph neutralization process. *Proceedings of Second European Control Conf*.ECC'93, 1993.Groningen, Netherlands.

[9] Piyush Shrivastava. Control of Nonliear Process using Neural Network Based model predictive Control , *IJEST 2011*